In Berthouze, L., Kozima, H., Prince, C. G., Sandini, G., Stojanov, G., Metta, G., and Balkenius, C. (Eds.)
Proceedings of the Fourth International Workshop on Epigenetic Robotics
Lund University Cognitive Studies, 117, ISBN 91-974741-3-4

Simulating development in a real robot: on the concurrent increase of sensory, motor, and neural complexity

Gabriel Gómez* **Max Lungarella**** **Peter Eggenberger Hotz***
Kojiro Matsushita* **Rolf Pfeifer***
*Artificial Intelligence Laboratory
Department of Informatics, University of Zurich, Switzerland
gomez@ifi.unizh.ch

**Laboratory for Intelligent Systems and Informatics
University of Tokyo, Japan
maxl@isi.imi.i.u-tokyo.ac.jp

Abstract

We present a quantitative investigation on the effects of a discrete developmental progression on the acquisition of a foveation behavior by a robotic hand-arm-eyes system. Development is simulated by (a) increasing the resolution of visual and tactile systems, (b) freezing and freeing mechanical degrees of freedom, and (c) adding neuronal units to the neural control architecture. Our experimental results show that a system starting with a low-resolution sensory system, a low precision motor system, and a low complexity neural structure, learns faster that a system which is more complex at the beginning.

1. Introduction

Development is an incremental process, in the sense that behaviors and skills acquired at a later point in time can be bootstrapped from earlier ones, and it is historical, in the sense that each individual acquires its own personal history (Thelen, 1999). It is well known that newborns and young infants have various morphological, neural, cognitive, and behavioral limitations, e.g., in neonates color perception and visual acuity are poor implying a poor tracking behavior; working memory and attention are restricted; and movements lack control and coordination. The state of immaturity of sensory, motor, and cognitive systems, a salient characteristic of development, at first sight appears to be an inadequacy.

Here, we argue that rather than being a problem, early morphological and cognitive limitations effectively decrease the amount of information that infants have to deal with, and may lead to an increase of the overall adaptivity of the organism. Such a theoretical position has been already pioneered by Turkewitz and Kenny (1982) more than 20 years ago. With respect to neural information processing, a similar point was made also by Elman (1993). More specifically, it has been suggested that by initially limiting the number of mechanical degrees of freedom that need to be controlled, the complexity of motor learning is reduced. Indeed, an initial freezing of degrees of freedom followed by a subsequent freeing might be the strategy figured out by Nature to solve the degrees of freedom problem first pointed out by Bernstein (1967), that is, the problem of why despite the highly complex nature of the human body, well-coordinated and precisely controlled movements emerge over time. The aim of this paper is to provide support for the hypothesis that "starting small" makes an agent more adaptive and robust against environmental perturbations.

Other attempts have shared explicitly or implicitly a similar research hypothesis. Nagai et al. (2003), for instance, applied a developmentally inspired approach to robotics in the context of joint attention. The effect of phases of freezing and freeing of mechanical degrees of freedom for the acquisition of motor skills was examined by Lungarella and Berthouze (2002). Although based on the same research hypothesis, the present study makes at least two novel contributions: (a) it considers concurrent "developmental changes" in three different systems, i.e., sensory, motor, and neural; and (b) it quantitatively compares a "developing" system to a "nondeveloping" system.

Obviously, an understanding of development cannot be limited to the investigation of control architectures only, but must include considerations on physical growth, change of shape, and body composition, which are salient characteristics of maturation.

Given the current state of technology, however, it is not easy to construct physically growing robots. We therefore propose a method to "simulate" development in an embodied artifact at the levels of sensory, motor, and neural system. In the following, we present quantitative results demonstrating how a concurrent increase of sensory resolution, motor precision and neural capabilities can shape an agent's ability to learn a task in the real world, and speed up the learning process.

2. Experimental setup

Our experimental setup consisted of: (a) an industrial robot manipulator with six degrees of freedom (DOF), (b) a color stereo active vision system, and (c) a set of tactile sensors placed on the robots gripper. As can be seen in Figure 1, joint $J0$ ("shoulder") was responsible for the rotation around the vertical axis, joint $J2$ ("elbow"), joint $J1$ ("shoulder") and joint $J3$ ("wrist") were responsible for the up and down movements; joint $J4$ ("wrist") rotated the gripper around the horizontal axis. The additional DOF came from the gripping manipulator.

3. Task specification

The task of the robot was to learn how to bring a colored object from the periphery of the visual field to the center of it through movements of its robotic arm. At the outset of each experimental run, the active vision system was initialized to look at the center of the visual scene (x_c, y_c), and the position of its motors were kept steady throughout the operation. The robot arm was placed at a random position in the periphery of the robot's visual field and a colored object was put in its gripper. Once the object was detected by the pressure sensors the robot started to learn how to move the arm in order to bring the object from the periphery of the visual field (x_0, y_0) to the center of it (x_c, y_c). For more details see Gómez and Eggenberger Hotz (2004).

4. Neural control architecture

The components of the neural structure and its connections to the robot arm are depicted in Figure 1. For more details see (Eggenberger Hotz et al., 2002; Gómez and Eggenberger Hotz, 2004).

4.1 Sensory field

The sensory field had three components: (a) *Color*: Neuronal units of area *RedColorField* (see Figure 1a) were active when the value of a "broadly" color-tuned channel for red: $R=r-(g+b)/2$ passed a given threshold θ_1, (b) *Motion detection*: Neuronal units of areas *RedMovementToRightField* (see Figure 1b) and *RedMovementToLeftField* (see Figure 1d) were active when the value of a motion detector reactive to red objects passed a given threshold θ_2, and (c) *Proprioceptive feedback*: The movements of each joint of the robot arm were encoded using eight neuronal units. Joint $J0$ had a range of movements from -60 to 60 degrees, joint $J1$ moved in a range from -25 to 25 degrees, and joint $J2$ moved in a range from 0 to 100 degrees.

4.2 Learning Mechanism

The active neurons controlling the robot arm were "rewarded" if the movement of the arm brought the colored object closer to the center of the visual field and "punished" otherwise. In this way the synaptic connections between the neuronal areas *NeuronalField* (see Figure 1e) and *MotorField* (see Figure 1f) were changed. A learning cycle (i.e., the period during which the current sensory input is processed, the activities of all neuronal units are computed, the connection strengths of all synaptic connections are updated, and the motor outputs are generated) had a duration of approximately 0.35 seconds.

5. Simulating development in a real robot

Because we are dealing with embodied systems, there are two dynamics, the physical one or body dynamics and the control one or neural dynamics. There is the deep and important question of how the two can be coupled in optimal ways. It has been hypothesized that given a particular task environment, a crucial feature of adaptive behavior is a balance between the complexity of an organism's sensor, motor, and control system (this is also referred to as principle of ecological balance) (Pfeifer and Scheier, 1999). Here, we extended this principle to developmental time, and attempted to comply to it by simultaneously increasing the sensor resolution, the precision of the motors, as well as the size of the neural structure. Such concurrent changes provide the basis for maintaining an adequate balance between the complexity of the three sub-systems, which reflects the development of biological systems.

The robot's movements were continuously shaped by the aforementioned learning mechanism, and "developmental" changes were triggered by the robot's internal performance evaluator (see definition of index "P" for the robot's task performance in Section 6.). Such changes consisted in advancing the present developmental stage (DS-$_i$) to the next one (DS-$_{i+1}$).

This was achieved as follows: (a) the resolution of the camera image was increased (by increasing the sharpness of a Gaussian blur lowpass filter applied to the original image capture by the cameras), and one or two pressure sensors were added, (b) another degree of freedom was released and came into op-

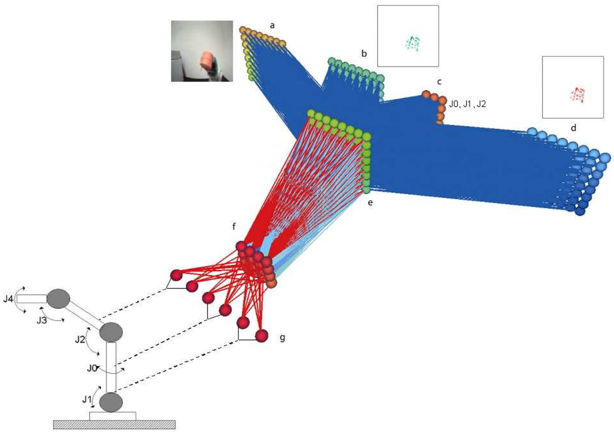

Figure 1: Neural structure and its connections to the robot's sensors and motors. Neuronal areas: (a) RedColorField. (b) RedMovementToRightField. (c) ProprioceptiveField. (d) RedMovementToLeftField. (e) NeuronalField. (f) MotorField. (g) MotorActivites.

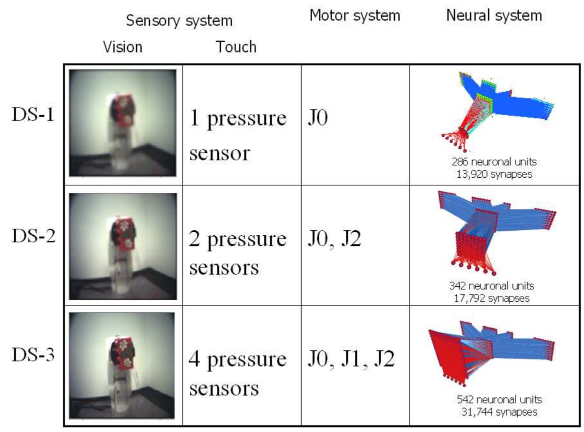

Figure 2: Configuration of the sensory, motor and neural components of the robot through the developmental approach. From top to bottom: DS-1 ("immature state"), DS-2 ("intermediate state") and DS-3 ("mature state").

eration, and (c) the size of the neuronal area "*ProprioceptiveField*" (see Figure 1c) was increased in 8 neuronal units, the size of the neuronal area "*MotorField*" (see Figure 1f) was increased by a factor of four. In order to preserve the previous knowledge acquired by the robot, the new weights were initialized randomly and the old weights were kept at their current values.

Figure 2 presents a summary of the configuration of the robot as well as the number of neuronal units in each neuronal area at each developmental stage. Through this simulated development (from DS-1 ("immature") to DS-3 ("mature")) the initial setup with reduced visual capabilities, low number of degrees of freedom, a few pressure sensors and a neural control architecture with a reduced number of neuronal units, was converted into an experimental setup with good vision, larger number of degrees of freedom, larger number of pressure sensors and a neural control architecture with a sufficient number of neuronal units. At developmental stage number 3 (DS-3), the robotic agent reaches the same sensory, motor and neural configuration than the control setup. At this point, their performances could be compared to see whether the learning was affected or not by the developmental approach described above.

6. Experiments and results

Figure 3 shows a typical experiment where the robot learned to move the object from the periphery of its visual field to the center of it by means of its robotic arm. To evaluate the change of the robot's task performance over time, at each time step i, we computed the cumulated distance covered by the center of the object projected onto one of the robot's cameras (x_i, y_i) as: $\hat{S} = \sum_{i=0}^{N-1} \sqrt{((x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2)}$. Thus, ($x_0$, y_0) is the initial position of the object as perceived by the robot, and (x_N, y_N) = (x_c, y_c) is the center of the robot's visual field (assuming that the robot learns to perform the task). The shortest possible path between (x_0, y_0) and (x_c, y_c) is defined as: $S = \sqrt{((x_0 - x_c)^2 + (y_0 - y_c)^2)}$. By using S and $\hat{S}$, we defined an index for the robot's task performance: $P = \frac{S}{\hat{S}}$. The closer P is to 1, the more straight the trajectory, and therefore the better the robot's behavioral performance. This performance criterion was always the same.

Figure 4 shows how the robot's behavior improved over time for the last part of the experiment number 1 (see Figure 3d) and gives the performance measure over time. A total of 15 experiments were performed with two types of robotic agents: one subjected to developmental changes (i.e., DS-1, then DS-2 and finally DS-3), and one fully developed since the onset (control setup). The results clearly show that the robotic agents that followed a developmental path took considerably less time to learn to perform the task. These robotic agents started with the configuration of the developmental stage "DS-1" and learned to solve the task during the learning cycle 483 ± 70 (where $\pm$ indicates the standard deviation), then they were converted to robotic agents with a configuration as described by the developmental stage "DS-2" which subsequently learned to solve the task around the learning cycle 1671 ± 102 and finally they become to be in the developmental stage "DS-3" (with the same configuration than the control setup) and solve the task around the learning cycle 4150 ± 149 (this is a cumulative value).
The control setup agents with full resolution camera images, four pressure sensor, three DOF (i.e., $J0$, $J1$ and $J2$), and a neural network with 542 neu-

ronal units (randomly initialized synaptic connections) learned to solve the task around the learning cycle 7480 $\pm$ 105. In other words, a reduction of about 44.5 percent in the number of learning cycles needed to solve the task can be observed in the case of robotic agents that followed a developmental approach when compared to the control setup agents.

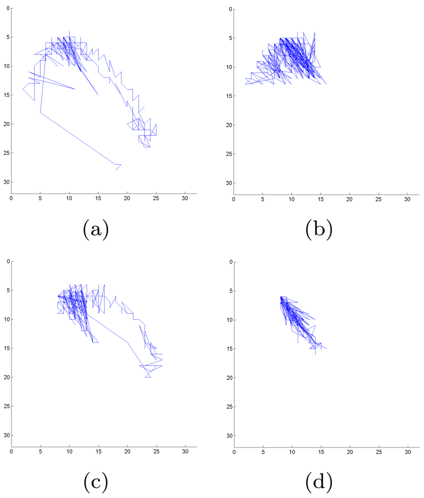

Figure 3: Experiment number 1. Learning to move a colored object from the upper left corner of the visual field to the center of it. Position of the center of the object in the visual field during the learning cycles in the interval (a) [1, 400]. (b) [401, 800]. (c) [801, 1200]. (d) [1201, 1602].

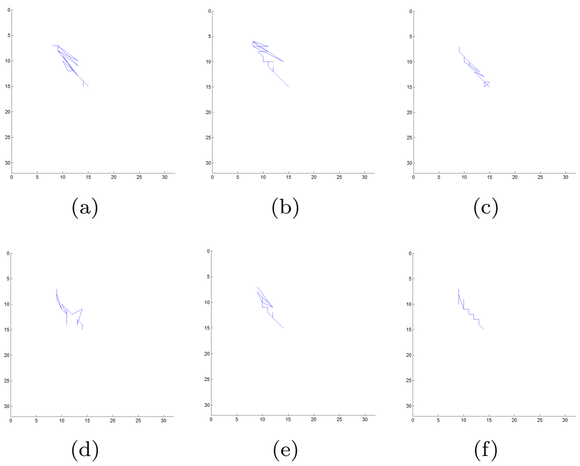

Figure 4: Robot's internal performance evaluator *"P"* during the learning cycles in the interval (a) [1232, 1266], P=0.2898; (b) [1313, 1340], P=0.3574; (c) [1370, 1393], P=0.5114; (d) [1438, 1455], P=0.5402; (e) [1502, 1519], P=0.6569;(f) [1565, 1582], P=0.9176. (see Figure 3d).

7. Discussion and conclusions

As shown by the results presented in this paper, a system starting with low resolution sensors and low precision motor systems, whose resolution and precision are then gradually increased during development, learns faster than a system starting out with the full high resolution high precision system from scratch. For this particular case, by employing a developmental approach the learning was speeded up by 44.5 percent. To our knowledge this is the first time that this point is actually shown in a quantitative way.

Acknowledgments

Gabriel Gómez was supported by the grant NF-10-101827/1 of the Swiss NSF and the EU-Project ADAPT (IST-2001-37173). Max Lungarella was sponsored by the University of Tokyo, and the Special Coordination Fund for Promoting Science and Technology from the Ministry of Education, Culture, Sports, Science, and Technology of Japan.

References

Bernstein, N. (1967). *The coordination and regulation of movements.* Pergamon, Oxford, England.

Eggenberger Hotz, P., Gómez, G., and Pfeifer, R. (2002). Evolving the morphology of a neural network for controlling a foveating retina - and its test on a real robot. In *Proc. of Artificial Life VIII*, pages 243–251.

Elman, J. (1993). Learning and development in neural networks: The importance of starting small. *Cognition*, 48:71–99.

Gómez, G. and Eggenberger Hotz, P. (2004). Investigations on the robustness of an evolved learning mechanism for a robot arm. In *Proc. of the 8th Int. Conf. on Intelligent Autonomous Systems (IAS-8)*, pages 818–827.

Lungarella, M. and Berthouze, L. (2002). On the interplay between morphological, neural and environmental dynamics: a robotic case-study. *Adaptive Behavior*, 10:223–241.

Nagai, Y., Hosoda, K., Morita, S., and Asada, M. (2003). A constructive model for the development of joint attention. *Connection Science 15*, 4:211–229.

Pfeifer, R. and Scheier, C. (1999). *Understanding Intelligence.* MIT Press.

Thelen, E. (1999). Dynamics mechanism of change in early perceptuo-motor development. In *Proc. of the 29th Carnegie Symposium on Cognition.*

Turkewitz, G. and Kenny, P. (1982). Limitation on input as a basis for neural organization and perceptual development: A preliminary theoretical statement. *Developmental Psychobiology*, 15:357–368.